Aalto University
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Trend factor revisited

Asset pricing factors over multiple investment horizons

Abstract

In this paper, I provide alternative formulations to the price trend factor of Han, Zhou and Zhu (2016), using returns instead of prices. The price trend factor is also constructed and compared with the return trend factors. Two market equity based factors were also constructed, but they showed little interest in themselves. Several tests were conducted that actually attested to the robustness and appeal of the price trend factor. The return trends showed each some weaknesses along the tests. The individual moving average lengths used in the factor construction were also explored and they revealed the adaptability of the price trend factor, which is the primary explanation of this study to the factor's good performance. For future research, the construction of other factors with the same method seem most fruitful.

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Contents

1 Introduction

One classical approach to explaining asset prices is a factor model, such as the capital asset pricing model (Sharpe, 1964; Lintner, 1965) and the Fama-French three-factor model (Fama and French, 1993). Many additional and alternative factors have been proposed in various studies. Han, Zhou and Zhu (2016), later HZZ, have created a trend factor with the intent of outperforming tree common factors based on past returns: momentum (Jegadeesh and Titman, 1993), short-term reversal (Lehmann, 1990; Jegadeesh, 1990) and long-term reversal (DeBondt and Thaler, 1985) factor. Their trend factor aggregates price information across multiple investment horizons from three days to a thousand days.

The construction method of the trend factor was based on several techniques that HZZ combined. Their main inspiration appears to have come from three sources; Haugen and Baker (1996) used the same factor construction method, where they used a cross-sectional regression on factor signals to produce coefficients – their equation 1 corresponds to the HZZ equation 3. Haugen and Baker also use a twelve-month average for smoothing the coefficients, which HZZ apply as well. On the other hand, HZZ calculate the signals for the using a broad array of normalized moving averages of prices. They take inspiration from Brock, Lakonishok and LeBaron (1992) who explored the use of simple trading rules – moving averages and trading-range breaks – to generate buy and sell signals. In this light, the trend factor can be interpreted as an application of the trading strategies into constructing an asset-pricing factor. HZZ extend the Brock et al. (1992) range of moving averages past 200 days all the way up to 1000 days. The third inspiration seems to come from their previous works,for example Han, Yang and Zhou (2013) on volatility-sorted investment timing portfolios and Zhu and Zhou (2009) on combining technical analysis with fixed asset allocation rules under information uncertainty. Many others also research the theme, and Glabadanidis (2015) provides a good example in considering trading costs, and taking a different angle in the portfolio construction with value weighting.

The HZZ study has shown that their trend factor has only a relatively low correlation with the short-term reversal factor, and an almost non-existent correlation with the momentum factor. It turned out that the trend factor was utilizing a different edge of the same phenomenon of price or return trends. One of the most prominent differenced HZZ identified was that the loser portfolio of the trend factor earned significantly better than that of the momentum factor. They attributed the good return characteristics of the trend factor across different economic conditions mainly to the low return of the loser portfolio compared to the momentum equivalent. As HZZ already comprehensively explored the winner–loser portfolio behaviours, this paper takes a different approach.

The purpose of this study is to explore the behaviour of the HZZ price trend factor in comparison to alternatives based on returns using the same methodology. The simple motivation is to see how a return-based version could challenge the complementary trio of return based single-horizon factors of short-term reversal, momentum and long-term reversal factors. A more general interest is to have a more comprehensive understanding on how the multi-horizon factors work. As the price trend factor proved different and relatively independent of the three return factors, the research question in this study is, whether a return trend factor be able to better cover the territory of the trio.

The remaining sections of this report are organised as follows. Section 2 presents a review of the current literature related to the trend factor. Section 3 describes the data, its filtering and representativeness. Section 4 discusses the methods for constructing the factors and Section 5 reports the methods for analysing and validating the research. Section 6 presents the research findings. Finally, section 7 concludes and suggests directions for further research.

Statistical software tools have differences between them in the calculation methods they employ, and therefore the software used may have its own effects on the results of the study. As the main software tool, I used the R-language and R-studio software, as well as different R-packages that extend the functionality of R. Along the sections I disclose the main R-packages and functions used, so that the results are more reproducible.

2 Data and data filtering

This section presents the data used in the study and the filtering process applied to the stock data. For filtering, I mostly used the *data.table* package and also the *foreach* package to some extent.

2.1 Data sources

Following HZZ, this study used daily and monthly stock time-series data from the Center for Research in Security Prices (CRSP), including only U.S. stocks (CRSP share codes 10 and 11). The sample period was from July 1, 1926 to December 30, 2016, in contrast to HZZ who used the period from January 2, 1926 to December 31, 2014.

The data library from Kenneth French's home page (French, 2017) was the source for NYSE breakpoints and the following factors: market excess return (MKT), risk-free rate (RF), market size (SMB), growth/value stock (HML), short-term reversal (SREV), momentum (MOM) and long-term reversal (LREV). HZZ also used these factors with the exception of the momentum factor. They derived it from equal-weighted momentum portfolio deciles, in contrast to the momentum factor from French's data library, which is based on the intersections of two market size and three prior return portfolios.

Since the data for the risk-free rate started from July 1, 1926 and it was required for calculating excess returns, CRSP data was cut to this date. Moreover, because the long-term reversal factor started from January 1931, the period for the analysis of factors was from January 1931 to December 2016, whereas HZZ used June 1930 to December 2014.

For defining the recession and expansion periods, the study used the business cycle table from the National Bureau of Economic Research (NBER, 2017). The financial crisis period followed HZZ and was from December 2007 to June 2009.

2.2 Data filtering process

The construction of the price trend factor and its analogues requires data from at least 1000 days plus 12 months. The shortest such interval was 1224 days. For a given last trading day of a month, there needed to be a price observation at least 999 days earlier, and each stock needed to have at least 12 (consecutive) such months.

Since many stocks had missing data, the following conditions were set for each of the months following the first 1000 days. For a month to be included in a factor quintile portfolio, more than 50 percent of the data must have valid adjusted price, return and cumulative return observation for each period length (3, 5, 10, 20, 50, 100, 200, 400, 600, 800 and 1000 days) as well as the tail of that period length behind the closest shorter period. Thus, for the 1000-day period, at least 501 observations were required, and for the earliest 200 days (the tail behind the 800-day period) at least 101 observations.

In addition, a valid monthly return of the next month was required for the regression in the factor construction. Each included stock had to have at least 12 such months. A more lenient requirement could have been that at least one such period of 12 months, in which at least the first and the last month passed the above missing data requirements, would be required. Finally, I applied size and price filters that excluded stocks below the 10 percent NYSE breakpoint and a price below 5 dollars. HZZ applied these filters as well, following the momentum strategy of Jegadeesh and Titman (1993).

Table 1: Stock data filtering

This table reports the original state of the stock data and the results of filtering for the period included in the study from June 1, 1926 to December 30, 2016.

The table includes the number of observed *days,* daily *return* observations*, months* across which the data spans*, months (signals)* with calculated factor signals, *months (portfolios)* included in the factor portfolios, *stocks,* unbroken *sequences* of required amount of data of the same stock and the *max sequences per stock*, which was the largest number of sequences of the same stock.

Data	original	filtered	filtered %
days	74 003 310	68 225 558	92 %
return	72 489 673	66 782 962	92 %
months	3 503 210	3 221 325	92 %
months (signals)		2 400 684	69 %
months (portfolios)		2 216 192	63 %
months (price filter)		1 779 060	51 %
months (size filter)		1 375 482	39 %
months (size and price)		1 330 954	38 %
stocks	24 482	15 254	62 %
sequences	24 482	16 733	68 %
stocks with 1 sequence		13 959	92 %
stock with 2 sequences		1 144	7,5 %
stock with 3 sequences		129	0,8 %
stock with 4 sequences		16	0,1 %
stock with 5 sequences		3	0,02 %
stock with 6 sequences		1	0,01 %
stock with 7 sequences		2	0,01 %

In this study, the initial filtering included only stocks that had at least 501 valid observation, as well as, met the 1000 days plus 12 months length requirement. In this filtered data, all months for all stocks passed the over-50-percent missing data requirements, although some were excluded due to missing return observation for the next month.

Furthermore, I omitted all such daily observations, where there would not be a complete set of adjusted price, return and cumulative return for the same day, although the day itself would remain in the data. This ensured that the different alternatives of the factor would base on the same amount of data

Table 1 presents the effect of the data filtering. Approximately 92 percent of the daily and monthly observations were included in the factor construction. Of all months, 69 percent had a calculated trend signal and the factor portfolios included 63 percent before the size and price filtering and 38 percent after it. Of all stocks, 62 percent were included, and most of them had one unbroken sequence, although, due to missing data, some stocks were broken into up to seven sequences.

Regarding the representativeness of the data, the calculations utilised 92 percent of the whole sample, which seems representative enough. The long data sequence lengths required by the moving averages reduced the pool of stocks by 20-30 percent and logically induced survival bias, as short-lived companies would fail to meet the requirement. The size filter had a considerable effect on the stock pool, and it caused purposeful bias by excluding smallest companies. As the portfolios use equal weighting, these two aspects counterbalance each other. The price filter resulted in little additional filtering beyond the size filter.

each stock for the month end (HZZ, Equation 4). In this multiplication, the month of the return (for example May), against which the previous month's (April) signals were regressed, is the same as the month of the signals (May). The sum of these products is the expected return of the stock for the next month (June). Hence, as HZZ denote, the factor is out-of-sample. Finally, they divide the stocks into equal-weighted quintile portfolios based on these expected returns, and the price trend factor is the difference between the actual return of the highest and the lowest quintile portfolio. HZZ

Let us now look more closely at the construction of the moving averages (compare Han et al. 2016, p. 334-335). First, we establish the relationship of price (P) and cumulative return (c) in Equation 2 and then apply it to the normalized three-day average in Equation 3:

$$P_{j,d} = \frac{P_{j,d} - P_{j,d-1}}{P_{j,d-1}} = P_{j,d-1} \cdot \left(1 + r_{j,d}\right) = P_{j,1} \cdot (1 + c_{j,d}), \quad where \left(1 + c_{j,d}\right) = \prod_2^d \left(1 + r_{j,d}\right) \qquad (2)$$

$$\tilde{A}_{j,t,3} = \frac{P_{j,d-2} + P_{j,d-1} + P_{j,d}}{3 \cdot P_{j,d}} = \frac{P_{j,1}\left((1+c_{j,d-2}) + (1+c_{j,d-1}) + (1+c_{j,d})\right)}{3 \cdot P_{j,1} \cdot \left(1+c_{j,d}\right)} = \frac{(1+c_{j,d-2}) + (1+c_{j,d-1}) + (1+c_{j,d})}{3 \cdot (1+c_{j,d})} \qquad (3)$$

where $P_{j,d}$ is the price, $r_{j,d}$ is the return, $c_{j,d}$ is the cumulative return of the whole stock time series, $\left(1 + c_{j,d}\right)$ is the cumulative return multiplier and $\tilde{A}_{j,t,N}$ is the normalized N-day MA-price of stock j in day d that is the trend signal. As we can see from Equation 3, analytically, the normalized average price is equal to the average cumulative return multiplier in proportion to the last day's value.

This study used cumulative returns (CRSP code *cumtret*) in place of split and dividend adjusted prices, to construct the price trend factor (TFC). The cross-sectional regression was a linear ordinary least squares (OLS) regression, using the *lm* function in base R.

3 Factor construction

This section describes the construction method of the price trend factor and its alternatives, gives economic interpretation of the different factor alternatives, introduces the other factors using the same construction methods and finally presents other factors constructed in this study.

3.1 Price trend factor construction

The method for constructing the multi-horizon factors in this study follows HZZ (pp. 334-335). They created their price trend factor from moving arithmetic averages of stock prices, adjusted for splits and dividends, using eleven period lengths (3, 5, 10, 20, 50, 100, 200, 400, 600, 800 and 1000 days). They calculate the moving averages (MAs) for the last trading day of each month (HZZ, Equation 1), and normalize them by dividing the average by the price of the last trading day (HZZ, Equation 2). These normalized MAs are the trend signals. HZZ

HZZ run a cross-sectional regression, where the signals explain stock returns of the next month for each month end (HZZ, Equation 3). It yields a time-series of coefficients for the signals, mutual for all stocks. Then they take a twelve-month average of each coefficient (HZZ, Equation 5) and multiply these averages by the respective signals of

3.2 Alternative trend factors

In this study, I used two principal alternatives to the price factor. The first alternative was based on returns instead of cumulative returns. The reasoning is that since the short-term reversal, momentum and long-term reversal factor are based on returns, it would make sense to construct a factor meant to capture the effect of these three factors from returns as well.

The second alternative was based on the geometric mean of returns, instead of the arithmetic mean. The purpose of this was to arrive at a distribution more similar to that of the price trend factor. If we assume that stock returns are normally distributed, the summation in the moving average of the first alternative preserves the distribution type. However, the price trend factor is composed of cumulative returns, which are multiplications of returns. Thus, they do not follow the normal distribution. The geometric mean of returns also has multiplication of returns, and thus is results in the same change in the distribution. Therefore, the second alternative serves as a comparison with similar distribution type. To calculate the geometric mean, I used the exponential of the mean of the logarithms of the return multipliers as in Equation 4:

$$e^{\frac{1}{N}\sum_{i=1}^{N}(1+r_i)} \tag{4}$$

I constructed four versions of both of the arithmetic return and geometric return alternatives: arithmetic return factor without normalization (IAF), with normalization (IAN), arithmetic excess return factor without normalization (XAF), with normalization (XAN), and their geometric mean counterparts (IGF, IGN, XGF, XGN). As the CAPM model implies, the stock is priced based on excess return rather than total return, therefore it seemed worthwhile investigating into the difference of between using either of these return types. To avoid the zero denominator problem, all the alternative factors used return multipliers $(1 + r)$.

3.3 Economic interpretation of the constructed factors

In the investor's point of view, the average of cumulative returns represents the expected return, if the investor purchased the stock at the beginning of the period and sold it on an arbitrary day within the period. Thus, the period length is analogous to the investor's reaction time i.e. the difference between the moment a new piece of information becomes available and the moment the investor can make a trade based on the new information. The average of returns, on the other hand, represents the expected one-day return on an arbitrary day within the period. Furthermore, a geometric mean of the returns represents the average daily return for the whole period. Thus, the explanatory power of these alternatives could shed the light to the way investor's process information.

The normalization of the MA-prices is necessary for making the signals stationary (Han et al., 2016). It also makes intuitive sense, as the normalized price average indicates whether the price has been better or worse before, reflecting the expected return (see the leftmost equality in Equation 2). In contrast, it is not necessary to normalize MA-returns, since returns are normalized by definition. The non-normalized MA-return reflects the expected return as well, whereas the normalized one reflects the relative expected return, indicating whether the return is better or worse than before. In other words, the normalized versions map the return trend of the stock.

3.4 Other multi-horizon factors

I also constructed two other factors with the multi-horizon method based on stock market equity, both with normalization. The purpose of these two factors was to see the effect of the factor construction method alone. One factor simply used market equity in place of the cumulative return of the price trend factor (TFC). Hence, it was practically a company growth trend factor (GRN), tracking how the market equity of the stock relates to its past. For the other factor, I calculated the proportion of market equity of the stock to the value-weighted average market equity of all stocks of the same day. This latter factor was thus a market equity factor (MEN) that resembled the SMB-factor of Fama and French (1993) in spirit.

4 Analysis methods

This section reports the different methods used for analysing and validating the constructed factors. I used some of the same tests HZZ used so that the results from this study could be compared to the original paper's results, as well as some others to delve deeper into the factors.

4.1 Basic analysis of the factors

First, I calculated the summary statistics of the constructed factors, as well as the most common factors (MKT, SMB, HML, SREV, MOM and LREV) used as reference points in HZZ. In addition to the metrics provided by HZZ, I calculated the Newey and West (1987; 1994, references provided by the package documentation) robust t-statistics and p-values for the robust significance levels, using the *NeweyWest* function in the *sandwich* package.

The summary statistics were a method of validating that the price trend factor I had constructed was indeed comparable to the HZZ trend factor. Comparing results of the other common, or control, factors to allowed to check the correctness of my calculations. In addition, it gave a first comparison with the alternative factors.

To explore the effect of extreme values, I constructed robust versions of the factors with median regression, which is less sensitive to outliers than the regular OLS regression. I conducted the median regression with the *rq* function with default settings in the *quantreg* package. The comparison between the regular and robust factors should reveal some of the effect extreme values had on the factors.

For further analysis of the factors, I also calculated correlation matrices.

4.2 Mean variance spanning tests

Following HZZ, I also conducted mean-variance spanning tests by regressing the trend factor against the three factors it was intended to replace (SREV, MOM and LREV), as well as more comprehensive sets of factors. HZZ provide a comprehensive set of six tests with different degrees of robustness, including three Wald tests.

I conducted a simpler test package, reporting the intercept of the regression, a robust t-statistic and significance, and two Wald tests with significance levels. For the robust t-statistic of the intercept, I used a kernel-based heteroscedasticity and autocorrelation consistent (HAC) covariance matrix estimator (Andrews, 1991, reference provided by the package documentation), for which the Newey and West HAC is a special case, with the *kernHAC* method of the *sandwich* package. I resorted to the kernel-HAC, because the Newey and West procedure showed warnings in the financial crisis period, suggesting there was not enough data for the method.

The two Wald tests utilised the *linearHypothesis* function of the *car* package. Following HZZ, I used the asymptotic Chi-squared distribution test the two Wald tests. I run one test with the default setting, which used a homoscedastic covariance matrix. For the other one, I applied a heteroscedasticity-consistent covariance matrix (HCCM) adjustment that uses the HCCM variant known as HC3, which is recommended by Long and Ervin (2000, reference provided by the package documentation). This was done using the *White.adjust* setting.

4.3 Individual and subset factors

To look closer into the individual MA-lengths of the trend factors, I also constructed separate factors from each MA-length, for some of the factors under analysis. I used the same coefficients from the cross-sectional regression of the full factor, but instead of summing up the products of each coefficient and the corresponding signal, I left them separate, and they were the expected returns for the individual factors. I used the same coefficients, because they are the constituents of the analysed factors. Had I regressed the signals of each MA-length separately, it would have analysed the MA-lengths in themselves and not their contribution to the full factor.

I calculated the most relevant summary statistics for the individual factors, and based them, I also constructed factors using two subsets of the MA-lengths, one with the most significant five lengths, which turned out to be the shortest ones (3, 5, 10, 20 and 50 days), and another one with the six remaining lengths (100 to 1000 days). I also provided correlation matrices to show the correlations between the full factor and the individual MA-lengths.

5 Results and analysis

In this section, I report the most relevant results from analysing the HZZ trend factor, the factors I have constructed and other common factors, including the Fama-French three-factors, short-term reversal, momentum and long-term reversal factor. The sample period for these calculations was from January 1931 to December 2016.

5.1 Summary statistics of the factors

In this subsection, I provide the essential summary statistics of the factors.

Table 2 presents the summary statistics for the price trend factor, its alternatives and the additional market equity related factors. The trend factor from cumulative returns (TFC) constructed in this study gives very similar results to HZZ, so it is fair to assume that the factor construction was successful. Looking at the alternative factors, they all are very similar to each other and to the TFC in broad terms. They have smaller returns in the whole sample (-0.21 – -0.12 %) and especially during the financial crisis (-0.59 – -0.15 %), whereas they yield ever so slightly more in recession (+0.02 – +0.09 %). The alternatives show a markedly higher excess kurtosis in the whole sample, with mixed results in the other periods.

Within the alternative factors, the return and excess return variants are virtually the same, which leads to the conclusion that the risk-free rate plays no role in this setting. Hence, I end the exploration of the excess return variants here. The arithmetic and geometric factors show differences, but they are not consistent. Similarly, within these

Table 2. Summary statistics of the price trend factor, its alternatives and other constructed factors.

This table reports the summary statistics for the price trend (*TFC*), non-normalized return (*IAF*), return (*IAN*), excess non-normalized return (*XAF*), excess return (*XAN*), non-normalized geometric mean return (*IGF*), geometric mean return (*IGN*), non-normalized geometric mean excess return (*XGF*) and geometric mean excess return (*XGN*) factors, as well as, market equity growth (*GRN*) and relative market equity (*MEN*) factors.

The reported statistics include sample mean in percentage (*mean*), t-statistic (*t-stat*), Newey-West robust t-statistic (*t-stat$_R$*), sample standard deviation (*sd*), Sharpe ratio (*sharpe*), skewness (*skew*) and excess kurtosis (*kurt*). For the t-statistics, significance at the 1, 5 or 10 percent level is given by ***, ** and ** respectively.

Factor	mean	t-stat		t-stat$_R$		sd	sharpe	skew	kurt
Panel A: Whole sample (1032 months)									
TFC	1,75	15,24	***	13,76	***	3,69	0,47	1,08	12,90
IAF	1,56	12,44	***	12,64	***	4,02	0,39	0,63	20,61
IAN	1,61	13,91	***	12,53	***	3,71	0,43	1,22	17,83
XAF	1,56	12,45	***	12,64	***	4,02	0,39	0,63	20,62
XAN	1,61	13,90	***	12,53	***	3,71	0,43	1,22	17,84
IGF	1,62	13,75	***	12,69	***	3,79	0,43	0,73	15,74
IGN	1,63	14,38	***	12,88	***	3,65	0,45	0,66	21,00
XGF	1,62	13,75	***	12,70	***	3,79	0,43	0,73	15,73
XGN	1,63	14,38	***	12,89	***	3,65	0,45	0,66	20,98
GRN	0,15	2,17	**	2,08	**	2,27	0,07	2,41	26,76
MEN	0,03	0,92		1,18		1,11	0,03	2,00	33,83
Panel B: Recession periods (186 months)									
TFC	2,57	6,12	***	7,06	***	5,46	0,47	0,10	6,23
IAF	2,59	5,78	***	6,27	***	5,81	0,44	-0,85	10,67
IAN	2,60	6,46	***	6,15	***	5,23	0,50	-0,17	6,51
XAF	2,59	5,78	***	6,27	***	5,81	0,44	-0,85	10,68
XAN	2,60	6,46	***	6,15	***	5,23	0,50	-0,17	6,52
IGF	2,66	6,06	***	5,79	***	5,71	0,47	-0,38	7,46
IGN	2,66	6,30	***	6,29	***	5,49	0,48	-0,90	10,96
XGF	2,66	6,06	***	5,79	***	5,71	0,47	-0,38	7,46
XGN	2,66	6,30	***	6,31	***	5,49	0,48	-0,90	10,96
GRN	0,00	0,02		0,02		2,61	0,00	0,18	4,44
MEN	0,00	-0,03		-0,07		1,54	0,00	-0,43	7,47
Panel C: Financial crisis (12/2007 - 06/2009, 19 months)									
TFC	1,23	0,86		1,18		6,20	0,20	0,87	0,19
IAF	0,99	0,68		0,87		6,33	0,16	-0,12	-0,36
IAN	0,80	0,59		0,81		5,92	0,14	0,12	-1,16
XAF	0,98	0,68		0,86		6,31	0,16	-0,15	-0,38
XAN	0,80	0,59		0,80		5,91	0,13	0,12	-1,15
IGF	1,08	0,80		1,06		5,89	0,18	-0,35	-0,92
IGN	0,64	0,53		0,99		5,22	0,12	-0,09	-1,34
XGF	1,07	0,79		1,04		5,91	0,18	-0,33	-0,93
XGN	0,64	0,54		1,00		5,21	0,12	-0,09	-1,34
GRN	0,03	0,08		0,11		1,78	0,02	0,11	-0,94
MEN	-0,09	-0,32		-0,26		1,26	-0,07	0,86	0,04

two groups, the normalized and non-normalized factors behave slightly differently. The market equity factors (GRN and MEN) fared poorly, although the GRN had a reasonable 5 percent significance, which questioned their usefulness altogether.

Table 3 provides the summary statistics for the control factors, including the Fama-French three-factors, short-term reversal, momentum and long-term reversal factors. In the whole sample, the small differences in the control factors are most likely due to the difference in the sample period. In the case of the momentum factor, the differences are larger, especially for the financial crisis. These are probably due to the different formulation in HZZ and this study. Therefore, this study complements the HZZ study, as it explores the price trend factor in the context of this different momentum factor formulation.

Table 3. Summary statistics of the control factors.

This table reports the summary statistics for the following control factors: the Fama-French three factors market excess returns (*MKT*), market size (*SMB*) and value/growth stocks (*HML*), as well as, the short-term reversal (*SREV*), the momentum (*MOM*) and the long-term reversal (*LREV*) factors.

The reported statistics include sample mean in percentage (*mean*), t-statistic (*t-stat*), Newey-West robust t-statistic (*t-stat$_R$*), sample standard deviation (*sd*), Sharpe ratio (*sharpe*), skewness (*skew*) and excess kurtosis (*kurt*). For the t-statistics, possible significance at the 1, 5 or 10 percent level is given by ***, ** and * respectively.

Factor	mean	t-stat		t-stat$_R$		sd	sharpe	skew	kurt
Panel A: Whole sample (1032 months)									
srev	0,79	7,34	***	6,78	***	3,46	0,23	1,00	8,35
mom	0,59	3,99	***	4,26	***	4,76	0,12	-3,13	27,90
lrev	0,33	3,04	***	2,42	**	3,48	0,09	2,94	24,93
mktrf	0,67	4,05	***	3,79	***	5,32	0,13	0,30	8,29
smb	0,27	2,69	***	2,60	***	3,23	0,08	2,01	19,84
hml	0,43	3,92	***	3,55	***	3,54	0,12	2,18	19,13
Panel B: Recession periods (186 months)									
srev	1,15	2,84	***	2,96	***	5,28	0,22	0,57	2,53
mom	0,28	0,44		0,43		8,18	0,03	-2,99	15,07
lrev	0,56	1,75	*	1,66	*	4,13	0,13	1,47	6,20
mktrf	-0,93	-1,47		-1,85	*	8,23	-0,11	0,55	4,10
smb	-0,10	-0,38		-0,48		3,33	-0,03	0,66	2,39
hml	0,25	0,60		0,64		5,36	0,05	2,84	17,57
Panel C: Financial crisis (12/2007 - 06/2009, 19 months)									
srev	-0,79	-0,61		-0,69		5,64	-0,14	-0,10	-1,14
mom	-1,34	-0,55		-0,47		10,55	-0,13	-1,65	3,20
lrev	0,02	0,02		0,02		3,69	0,00	0,15	-0,46
mktrf	-2,03	-1,25		-1,12		7,07	-0,29	-0,19	-0,48
smb	0,59	1,15		1,48		2,26	0,26	0,21	-1,00
hml	-0,53	-0,51		-0,43		4,51	-0,12	-0,48	0,10

5.2 Robust factors and extreme values

Table 4 presents the summary statistics for the robust factors, which include all the constructed factors. In the whole sample, the robust factors have similar returns as their regular counterparts. In the extremes, the price trend factor had a 0.06 % lower return, whereas the geometric non-normalized return factor (IGF) earned 0.04 % more. In the recession period, all factors showed clearly lower returns, 0.37 to 0.16 % decrease. In the financial crisis, all the return-based factors show negative returns, whereas the TFC remains slightly positive (0.02 %). The drop is rather dramatic, ranging from 1.01 % for the TFC to 1.60 % for the IGF, suggesting that extreme values play a more salient role in the returns during times of economic hardship.

For the other statistics, the standard deviation or volatility stayed relatively similar, whereas the Sharpe ratio fell as the returns fell. TFC shows a clear decline in skewness for all periods. The TFC also showed a considerable bump in excess kurtosis, almost doubling the value in the whole sample and in recession. The larger excess kurtosis suggests that the robust factor contained more extreme values, and the reduced skewness that they were more towards the negative side. This should result in a lower return, which it does, except for the whole sample.

In the expansion periods, the returns for the regular and robust TFC were 1.59 and 1.69 percent, the skewness measures 1.58 and 2.27 and the excess kurtoses 15.60 and 7.75, respectively. Thus, in expansions, the robust factor had a larger positive skewness and less excess kurtosis and benefited from a higher return. The return factors showed mixed tendencies in the expansion periods, and their returns stayed between 1.35 and 1.49 % in both regular and robust factors.

Overall, it seems that the TFC better picks profitable stocks than the return factors. The factor benefits considerably from extreme values during economically difficult times, and suffers only a little in better times, which makes the factor return relatively consistent across different economic conditions. The market equity factors continued to perform poorly and reached no meaningful significance.

Table 4. Summary statistics of the robust factors.

This table reports the summary statistics for the robust price trend (*TFC*), non-normalized return (*IAF*), return (*IAN*), excess non-normalized return (*XAF*), excess return (*XAN*), non-normalized geometric mean return (*IGF*), geometric mean return (*IGN*), non-normalized geometric mean excess return (*XGF*) and geometric mean excess return (*XGN*), as well as, market equity growth (*GRN*) and relative market equity (*MEN*) factors.

The reported statistics include sample mean in percentage (*mean*), the difference between the regular and robust factor mean as $mean_{regular} - mean_{robust}$ (*diff*), Newey-West robust t-statistic (*t-stat$_R$*), sample standard deviation (*sd*), Sharpe ratio (*sharpe*), skewness (*skew*) and excess kurtosis (*kurt*). For the t-statistic, possible significance at the 1, 5 or 10 percent level is given by ***, ** and * respectively.

Factor	mean	t-stat		t-stat$_R$		sd	sharpe	skew	kurt
Panel A: Whole sample (1032 months)									
tfc	1,81	15,98	***	13,55	***	3,63	0,50	0,63	22,21
iaf	1,52	12,63	***	12,32	***	3,87	0,39	0,23	17,17
ian	1,63	14,32	***	12,05	***	3,65	0,45	1,03	17,33
igf	1,58	12,77	***	11,62	***	3,98	0,40	-0,13	19,78
ign	1,64	14,61	***	12,75	***	3,60	0,45	0,13	19,83
grn	0,05	0,70		0,72		2,26	0,02	1,79	21,39
Panel B: Recession periods (186 months)									
tfc	2,41	5,50	***	5,42	***	5,70	0,42	-1,03	13,53
iaf	2,30	5,16	***	4,94	***	5,81	0,40	-0,75	10,25
ian	2,50	6,09	***	5,62	***	5,34	0,47	0,15	7,27
igf	2,29	4,93	***	4,27	**	6,05	0,38	-0,78	8,70
ign	2,39	5,56	***	5,33	***	5,58	0,43	-0,63	11,98
grn	-0,01	-0,06		-0,07		2,76	0,00	-0,24	1,97
Panel C: Financial crisis (12/2007 - 06/2009, 19 months)									
tfc	0,22	0,16		0,21		5,97	0,04	0,28	-0,56
iaf	-0,50	-0,39		-0,61		5,61	-0,09	-0,21	-0,73
ian	-0,30	-0,31		-0,85		4,30	-0,07	0,19	-0,55
igf	-0,53	-0,31		-0,41		7,36	-0,07	-0,32	-0,93
ign	-0,67	-0,59		-0,75		4,94	-0,14	0,22	-0,44
grn	-0,16	-0,22		-0,34		3,07	-0,05	0,01	-0,40

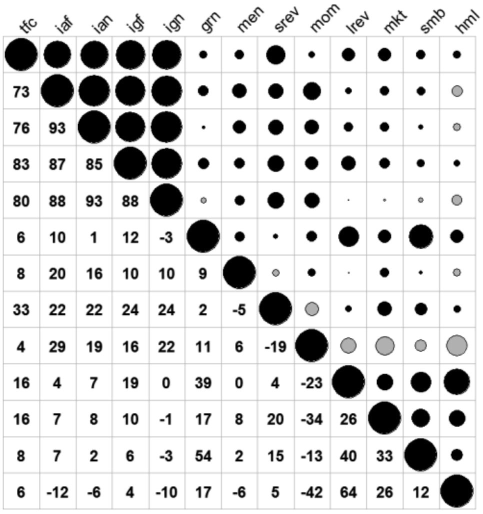
5.3 Correlation matrices

This subsection explores the correlation between the factors under study.Figure 1 shows the correlation matrix of

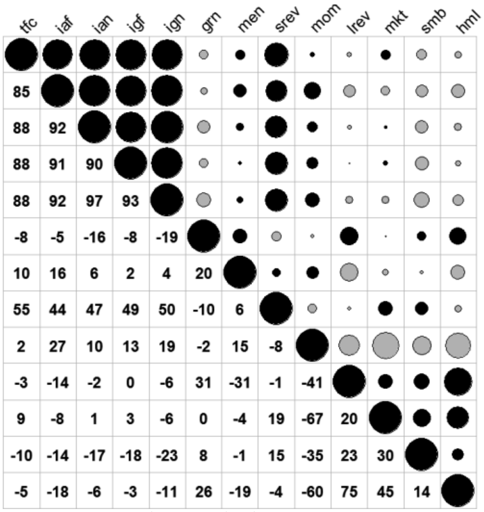
the whole sample period for all the factors in the study. Unsurprisingly, the price and return trend factors showed high correlations with each other. Of the SREV, MOM and LREV factors, the SREV correlated most strongly with the trend factors, having a 0.33 correlation with the TFC and a 0.22 to 0.24 correlation with the return factors. MOM was virtually uncorrelated (0.04) with TFC, whereas it was clearly correlated (0.16 to 0.30) with the return factors. The LREV, on the other hand, correlates more with TFC (0.16) and the IGN (0.19) than the other return factors (0.00 – 0.07). The control factors had mostly small to medium correlations with all factors, although they had higher positive or negative correlations with each of the than with the trend factors. MOM had a negative correlation with all other control factors. The growth factor (GRN) exhibited positive correlations with the control factors, while the market equity factor (MEN) correlated, albeit to a small degree, with the trend factors.

For the recession periods, in Figure 2, the correlations remained very similar. The SREV factor had a much stronger correlation with the trend factors around 0.50, while the other control factors had lower correlations than in the whole sample, although SMB had a clear negative correlation with the trend factors. In the financial crisis (Figure 3), the picture changed. The market equity factors exhibited an intermediate correlation with the trend factors and the Fama-French three-factors. The most notable change is that SREV, MOM and especially LREV showed strong negative correlations with the trend factors, which was also the case for HML. Momentum correlated negatively with the Fama-French three-factors across all periods.

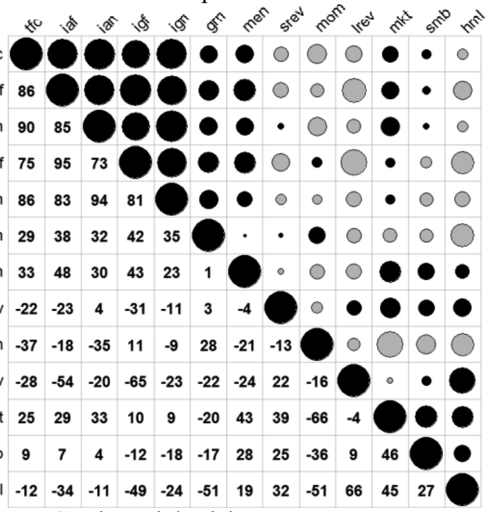
The correlations showed that the trend factors reacted in a different way from the return-based SREV, MOM and LREV to the financial crisis. Perhaps it was due to their multi-horizon nature that might have allowed them to tap into the long or short term changes depending on the economic conditions



Frame A: Whole sample period



Frame B: Recession periods



Frame C: Financial crisis

Figure 1: Correlation matrices of the factors.

Order of the factors in each matrix, left-to-right and top-to-bottom: TFC, IAF, IAN, IGF, IGN, GRN, MEN, SREV, MOM, LREV, MKT, SMB and HML.

The circle area corresponds to the correlation, black and grey indicate positive and negative correlation, respectively. Coefficients are in percentages.

Table 5. Mean-variance spanning tests for the price trend factors and its alternatives.

This table reports the results of mean-variance spanning tests with the price trend (*TFC*), non-normalized return (*IAF*), return (*IAN*), non-normalized geometric mean return (*IGF*), geometric mean return (*IGN*) factors as the test assets. Each of them is spanned against the short-term reversal (*SREV*), momentum (*MOM*) the long-term reversal (*LREV*) factors.

The reported statistics include spanning regression intercept in percentage (*int*) and kernel-HAC corrected robust t-statistic ($t\text{-}stat_R$), Wald test under conditional homoscedasticity (*wald*) and Wald test under conditional heteroscedasticity, with the HC3 heteroscedasticity-consistent covariance matrix ($wald_R$). Both Wald-tests have an asymptotic Chi-squared distribution. For the t-statistic and the Wald tests, possible significance at the 1, 5 or 10 percent level is given by ***, ** and * respectively.

Factor	int	$t\text{-stat}_K$		wald		$wald_R$	
Whole sample (1032 months)							
TFC	1,32	9,70	***	147,58	***	85,86	***
IAF	1,07	7,20	***	81,50	***	49,33	***
IAN	1,22	9,47	***	127,47	***	65,65	***
IGF	1,16	9,19	***	105,67	***	64,71	***
IGN	1,24	9,96	***	145,75	***	66,86	***
Recession periods (186 months)							
TFC	1,89	4,95	***	28,17	***	17,63	***
IAF	1,94	4,50	***	24,42	***	18,97	***
IAN	1,99	5,57	***	30,43	***	20,31	***
IGF	1,92	5,54	***	24,00	***	18,94	***
IGN	1,96	5,57	***	28,08	***	20,88	***
Financial crisis (12/2007 - 06/2009, 19 months)							
TFC	0,71	0,75		20,85	***	5,31	*
IAF	0,64	0,69		30,12	***	6,83	**
IAN	0,55	0,65		12,92	***	4,74	*
IGF	0,93	1,07		35,17	***	10,47	***
IGN	0,49	0,54		12,19	***	5,69	*

5.4 Mean-variance spanning tests

In this subsection, I discuss the mean-variance spanning test results. All spanning tests have the same regression restriction, or null-hypothesis, as in HZZ, where the intercept is zero and the sum of the coefficients is one.

Table 5 presents the first mean-variance spanning tests where the explanatory variables were the trio of SREV, MOM and LREV factors. All factors had the strongest scores in the whole sample, probably due to the larger amount of data. The unexplained return or the alpha that the intercept represents was highest in recession, suggesting the explanatory assets cannot explain the profits of the trend factors very well during recession.

The price trend (TFC) and the geometric return (IGN) factor had the strongest test scores in the whole sample, and they did well in the recession period as well, although the arithmetic return factor (IAN) had the highest test scores in recession. Financial crisis took a toll on the normalized return factors that were the weakest, while the non-normalized factors increased their test scores above their recession scores. IGF was especially strong and had a higher intercept than the rest. It was also relatively even in performance compared to the other return trend factors. The TFC performed well across the board.

Table 6 presents to additional spanning tests where in the Panel A test, the TFC factor was added to see how it can span the return trend factors. In Panel B, the return trend factors spanned the TFC and other return trend factors, and the panel reports the average result of spanning with each of the four factors as the added factor. The results were clear; the TFC had much higher spanning power in relation to the resistance power, or uniqueness of the return factors. Hence, the TFC seems to span wider and thus be a more usable factor. The return factors showed similar relative strengths in the different economic conditions across the three spanning test versions.

I also conducted spanning tests with the market equity based factors (GRN and MEN) but their spanning power was almost non-existent. However, when either one of them was combined with the IGN factor, the TFC test scores became somewhat less impressive, as the robust Wald score went down to 15.42 and 13.19 for GRN and MEN, respectively. When I added either of them with the TFC, the IGN was the most resistant of the return trend factors, typically having a 1 or 5 percent significance in the robust Wald test, whereas the others hardly ever reached even the 10 percent level.

5.5 Individual and subset factors

This subsection explores the individual MA-lengths of the constructed factors and factors using subsets of the MA-lengths.

Table 7 reports the summary statistics for the individual factors, the subset factors for the five shortest MA-lengths (Short) and the six longest MA-lengths (Long) and the full factor (All) with all MA-lengths, for the price trend factor and the return factors. In general, the TFC and especially the non-normalized return factors (IAF, IGF) had the highest returns and correlations in the shortest MA-lengths. The significance levels were also the highest for the shortest periods, although the 5-day factor made an exception with the TFC. There was a stark contrast between the short and the long MA-lengths in the TFC, as the longer end showed returns close to zero. The IAF and IGF showed relatively consistently declining returns as the period lengths increased.

The returns of the normalized return factors (IAN, IGN) were more consistent in absolute terms, and the 200-day mark even showed a strong significance at the 1 percent level. In the geometric version (IGN), the significance is at the 5 percent level even for the longest MA-lengths, although the 100-day and 600-day lengths are insignificant.

Perhaps these differences in being either short-term or long-term reflect the different nature of the factors. Contrary to the ideas presented in the section 3.3 Economic interpretation of the constructed factors, the normalization seems to be the leading explanation to the differing salience of the long and short time intervals among the return factors.

5.6 Individual factor correlations

Figure 2 shows the correlations of the full factor with the individual factors. Broadly speaking, the correlations were highest, in absolute terms, during the financial crisis, and showed most dispersion, whereas the patterns were much cleaner and tighter in the whole sample. The recession periods were somewhat of an intermixture of the two other periods, and had a clear increase in correlations in the shorter end of the MA-lengths (top left corner of the matrices) especially with the geometric factors (IGF and IGN), while the correlations the longer horizons tended to increase even further in the financial crisis. The longer end also demonstrated a curious pattern where the sign of the correlation tended to switch with every step.

In analysing the correlation of the full factor with its constituent individual factors, the full TFC factor showed highest correlations for the same MA-lengths (3, 10 and 50 days) that yielded the highest returns (Table X). The non-normalized return factors exhibited a similar relation as the shortest MA-lengths had the highest correlations with the full factors. On the other hand, the normalized return factors showed much lower absolute correlations with the individual factors, as evident by the almost empty rows in the top left corner, and a more even spread just as in the returns.

In recession, the full factor correlation patterns with the individual factors were very similar. For TFC, IAF and IGF the contrast between high correlation in the short end and low in the long end become slightly more pronounced. Moreover, with IAN and IGN, the highest absolute correlations seemed to concentrate around the 50-day and adjacent MA-lengths.

Table 6. Mean-variance spanning tests.

This table reports the results of mean-variance spanning tests. Panel A test assets are the price trend (*TFC*), non-normalized return (*IAF*), return (*IAN*), non-normalized geometric mean return (*IGF*), geometric mean return (*IGN*) factors as the test assets. Each of them is spanned against the short-term reversal (*SREV*), momentum (*MOM*) amd long-term reversal (*LREV*) factor. Panel A reports the spanning with the TFC factor included. Panel B reports the average of the four tests with the added factor being the IAF, IAN, IGF and IGN in turn in stead.

The reported statistics include spanning regression intercept in percentage (*int*) and kernel-HAC corrected robust t-statistic ($t\text{-}stat_R$), Wald test under conditional homoscedasticity (*wald*) and Wald test under conditional heteroscedasticity, with the HC3 heteroscedasticity-consistent covariance matrix ($wald_R$). Both Wald-tests have an asymptotic Chi-squared distribution. For the t-statistic and the Wald tests, possible significance at the 1, 5 or 10 percent level is given by ***, ** and * respectively.

Factor	int	$t\text{-}stat_K$		wald		$wald_R$	
Panel A: Factor = SREV + MOM + LREV + TFC							
Whole sample (1032 months)							
IAF	0,05	0,48		0,95		0,45	
IAN	0,21	2,17	**	14,04	***	4,74	*
IGF	0,06	0,73		4,32		2,19	
IGN	0,19	2,01	**	24,76	***	5,31	*
Recession periods (186 months)							
IAF	0,24	0,95		1,89		1,95	
IAN	0,38	1,82	*	3,22		2,51	
IGF	0,21	0,80		5,78	*	4,37	
IGN	0,33	1,42		5,23	*	5,36	*
Financial crisis (12/2007 - 06/2009, 19 months)							
IAF	0,06	0,09		3,72		2,02	
IAN	-0,11	-0,23		0,91		0,33	
IGF	0,43	0,71		6,00	**	4,05	
IGN	-0,11	-0,31		0,68		0,27	
Panel B: Factor = SREV + MOM + LREV + Return factor							
Whole sample (1032 months)							
TFC	0,00	4,62	***	40,80	***	23,89	***
IAF	0,00	-0,83		23,02		5,24	
IAN	0,00	3,04		41,93		15,49	
IGF	0,00	2,16		29,19	***	8,43	**
IGN	0,00	3,49	**	63,75	***	15,82	**
Recession periods (186 months)							
TFC	0,00	1,52		5,33		2,45	
IAF	0,00	0,54		1,77		0,64	
IAN	0,00	1,94		9,85	**	4,54	
IGF	0,00	0,60		2,83		1,89	
IGN	0,00	1,15		6,11	*	3,22	
Financial crisis (12/2007 - 06/2009, 19 months)							
TFC	0,00	0,28		2,72		1,06	
IAF	0,00	-0,36		10,58	*	5,11	
IAN	0,00	-0,27		3,63		2,92	
IGF	0,00	1,10		16,02	**	7,97	*
IGN	0,00	-0,32		2,64		2,72	

In the financial crisis, there were large changes; all factors favoured the 5-day lengths. TFC showed over 0.80 correlation for the 3- and 5-day lengths. The 10-day length shifted to strong negative correlations, a complete flip of the table for TFC, IAF and IGF. The geometric factors had over 0.80 negative correlation to 10 days, and TFC had a negative 0.60 correlations. On the other hand, the correlations in the long end also were much stronger, especially with the geometric factors. Overall, it seems that the TFC was liveliest in changing correlations depending on the economic conditions. The geometric factors were also relatively sensitive.

I decided to construct the subset factors as the pattern emerged, where the shortest MA-lengths showed much higher returns and significance than the long ones. I based the choice on the significance levels in order to find out, if choosing the most versus the least significant MA-lengths would make a difference in the returns. I also deemed it necessary to have a common subset for all the alternatives, as cherry picking different MA-lengths might have been less useful for analysis.

The Short factors earned almost as much as the full factors, while the Long factors had much lower return. Consistent with the significance level patterns, the normalized return factors showed a smaller decline in returns for the Long factors. It is also noteworthy that, among the individual factors, the standard deviations were much lower for the normalized return factors, and the differences disappeared in the full and the subset factors.

Reflecting the results of HZZ who stated that the 20-, 100- and 200-day MA-lengths were some of the most important ones for the price trend factor, the correlation matrices seem to suggest otherwise. The TFC especially seemed to skip the 20-day length, and started to correlate with the 100-day mark in the recession, whereas the 200-day period came along only in the financial crisis. On the other hand, separate analysis of the winner and loser portfolios might have given a different picture. It was precisely the loser portfolio, where the momentum and the price trend factor were most uncorrelated according to HZZ.

Table 7. Summary statistics of the individual, subset and full factors.

This table reports the summary statistics of the price trend (*TFC*), non-normalized return (*IAF*), return (*IAN*), non-normalized geometric mean return (*IGF*), geometric mean return (*IGN*) factors. For each factor the individual constituent factors of different MA-lengths ranging from *3* to *1000* days, the subset factor including the five shortest MA-lengths from 3 to 50 days (*Short*) and the subset factor including the six longest MA-lengths from 100 to 1000 days (*Long*), and the respective full factors with all MA-lengths (*All*) are given.

The reported statistics include sample mean in percentage (*mean*), the possible significance level based on the Newey-West robust t-statistic at the 1, 5 or 10 percent level is given by ***, ** and * respectively and sample standard deviation (*sd*).

	TFC			IAF			IAN			IGF			IGN		
Days	mean		sd	mean		sd	mean		sd	mean		sd	mean		sd
All	1,75	***	3,69	1,56	***	4,02	1,61	***	3,71	1,62	***	3,79	1,63	***	3,65
Short	1,59	***	3,73	1,44	***	3,82	1,47	***	3,23	1,50	***	3,91	1,45	***	3,34
Long	0,95	***	4,25	0,60	***	4,10	1,18	***	3,49	0,72	***	3,79	1,23	***	3,52
3	0,95	***	2,96	1,36	***	3,12	-0,44	***	2,46	1,39	***	3,16	-0,53	***	2,44
5	0,33	*	3,48	0,93	***	3,30	-0,45	***	2,57	1,01	***	3,29	-0,51	***	2,56
10	0,77	***	3,69	0,86	***	3,84	-0,67	***	2,66	0,91	***	3,81	-0,69	***	2,62
20	0,43	***	4,07	0,72	***	4,04	-0,49	***	2,70	0,84	***	4,09	-0,71	***	2,64
50	0,91	***	4,46	0,32	**	4,39	-0,22		2,84	0,55	***	4,47	-0,35	**	2,80
100	-0,12		4,87	-0,17		4,74	-0,06		2,81	0,13		4,95	-0,11		2,78
200	0,06		5,50	0,23		5,13	0,50	***	2,76	0,24		5,61	0,62	***	2,74
400	0,04		5,86	0,06		5,15	0,32	**	2,80	-0,02		5,55	0,28	**	2,74
600	0,05		5,89	-0,05		5,00	-0,01		2,78	0,04		5,53	-0,02		2,78
800	0,11		6,02	-0,10		4,79	-0,26		2,74	-0,07		5,35	-0,36	**	2,74
1000	0,01		5,94	0,20		4,56	-0,08		2,79	0,26		4,94	0,26	**	2,77

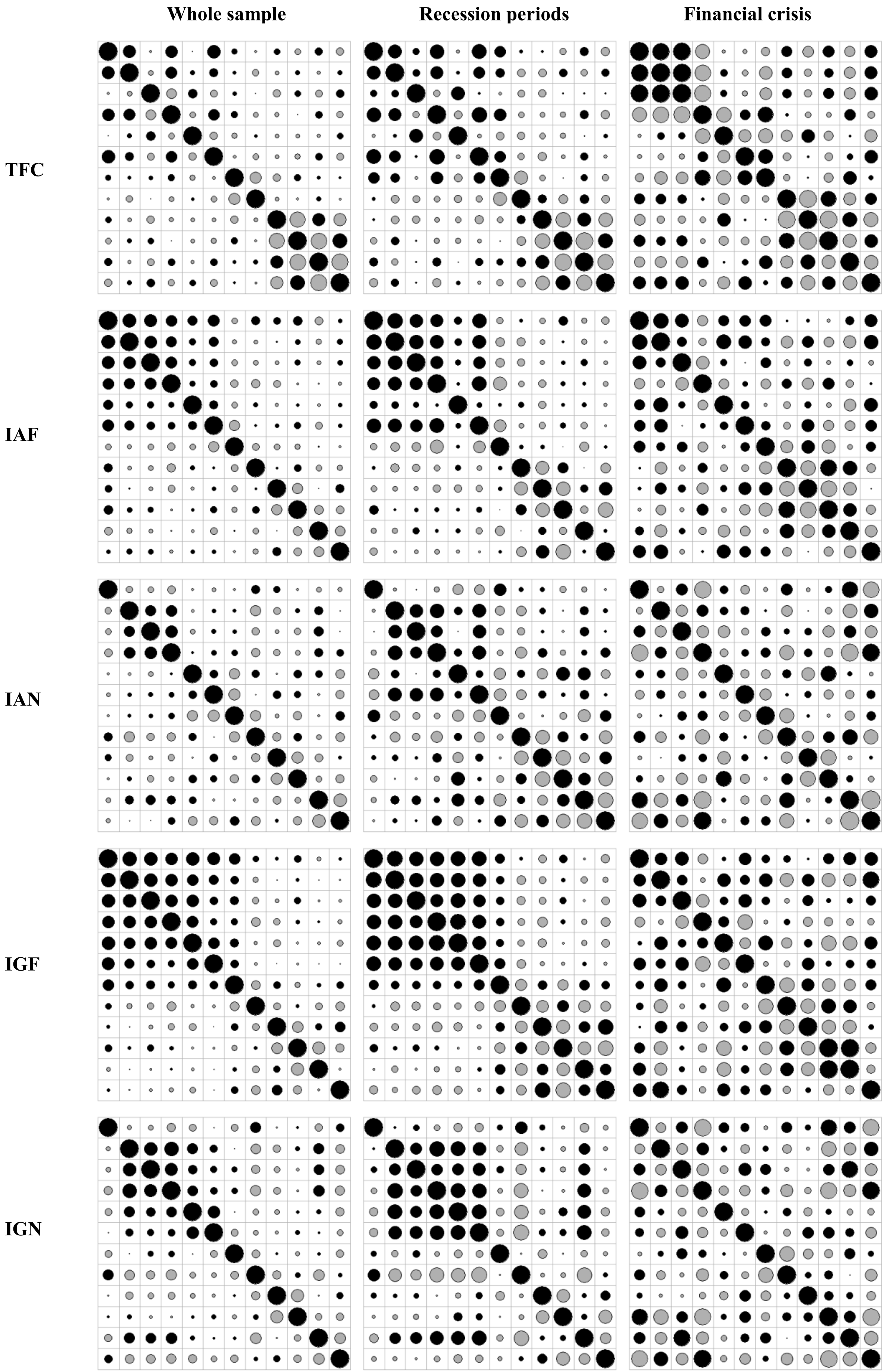


Figure 2: Correlation matrices of correlations between the full factor and its constituent individual factors. Factors include TFC, IAF, IAN, IGF and IGN. Order of the factors in each matrix, left-to-right and top-to-bottom: Full 3- to 1000-day individual factors. Circle area is the correlation; black is positive and gray is negative correlation.

7 Conclusions

The purpose of this paper was to explore, if and alternative version of the Han et al. (2016) price trend factor, constructed from returns instead of prices, could be successful in challenging the three complementary factors, short-term reversal, momentum and long-term reversal factors. A secondary objective was to further explore the performance of the price trend factor against the return trend factors created in this study.

The study included several tests, partly following HZZ. The summary statistics showed that the price trend factor was more consistent across different economic conditions than the return factors, although the latter showed slightly better returns in recession periods. The robust versions of the factors helped in understanding how the price trend factor (TFC) was able to perform so well in differing economic conditions by revealing how the extreme returns affect the factors. The TFC seemed to be balanced towards gaining a boost in the economically challenging times, especially the financial crisis.

The TFC seemed to be able to switch between the short and long timespan of the different moving average lengths, mapping out effectively opportunities for returns across economic cycles. This ability was clear in the correlation matrices of the factors where the TFC showed a more varied pattern of dispersion within each period as well as between periods.

Perhaps the most novel part of this study in relation to HZZ was the construction and analysis of individual MA-length factors. They revealed the different timing patterns of the trend factors, where the non-normalized versions stressed heavily the short MA-lengths, and the normalized versions were more dispersed. The price trend factor was again in the middle ground, attesting to its ability to adjust to different conditions.

The mean-variance spanning tests further strengthened the position of the price trend factor, as it was stronger and showed a higher level of uniqueness than the return factors, and again showed a relatively good resilience or robustness to economic conditions.

The study also utilised two market equity based multi-horizon factors, but they provided little to the study. However, they suggest an interesting direction for future research, namely the construction of other factors with the same multi-horizon methodology. Another possibility would also be to use control factors in the cross-sectional regression of the factor construction, which might be a method to calibrate a factor for use with specified control factors. One especially intriguing possibility could be to use skewness or excess kurtosis as the basis for the trend signals.

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